

# ISEF Project Roadmap: Physics-Informed Neural Networks for Orbital Propagation

**Project Goal:** Develop a High-Fidelity Orbital Propagator using Physics-Informed Neural Networks (PINNs) to outperform standard AI models in predicting satellite trajectories.

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## Phase 1: The Foundation (Data Generation)

**Goal:** Create the "Ground Truth" dataset. We cannot train an AI without knowing the correct answers first.

### Role: The Mathematician

- **Verify the Constants:** Confirm we are using the correct gravitational parameter for Earth ( $\mu = 3.986 \times 10^5 \text{ km}^3/\text{s}^2$ ) and Earth's radius ( $R_E = 6378 \text{ km}$ ).
- **The Equation Check:** Verify that the Two-Body Equation of Motion is correctly formulated for the code:  
$$\ddot{\mathbf{r}} = -\frac{\mu}{|\mathbf{r}|^3} \mathbf{r}$$
- **Units:** Ensure all data is consistent (km and seconds). Neural networks struggle with huge numbers, so we may need to normalize this later (e.g., divide distances by Earth's radius).

### Role: The Coder

- **Environment Setup:** Install `numpy`, `scipy`, `torch`, `matplotlib`.
- **Script Implementation:** Write and run the `generate_data.py` script (provided in chat).
- **Data Generation:**
  - Simulate a Low Earth Orbit (LEO) for 3 orbital periods.
  - Save the output (`t`, `x`, `y`, `z`, `vx`, `vy`, `vz`) to `orbital_data.npy`.
- **Sanity Check:** Plot the generated data in 3D. If the orbit isn't a closed ellipse, do not proceed.

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## Phase 2: The "Straw Man" (Baseline Model)

**Goal:** Build a "dumb" standard neural network that fails. This establishes a baseline to prove why the PINN is necessary.

### Role: The Mathematician

- **Define the Metric:** specific strictly how we measure "failure."
  - Metric: Root Mean Square Error (RMSE) of position over time.
- **Analyze the Drift:** When the standard model fails, does it break Conservation of Energy? Calculate the specific energy at the point of failure to prove it violates physics.

### Role: The Coder

- **Build the MLP:** Create a standard Multi-Layer Perceptron in PyTorch.
  - Input: Time ( $t$ ).
  - Hidden: 3 layers  $\times$  64 neurons (Tanh activation).
  - Output: Position ( $x, y, z$ ).
- **The "Black Box" Training:** Train this model on the first 80% of the orbit data using only **MSE Loss** (Mean Squared Error).
- **The Failure Plot:** Ask the model to predict the final 20% of the orbit. Plot the prediction vs. the ground truth. It should diverge significantly. **Save this plot for the science fair board.**

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## Phase 3: The PINN (Physics-Informed Core)

**Goal:** The core innovation. Teaching the AI the laws of physics using a custom loss function.

### Role: The Mathematician

- **Derive the Residual:** Write the exact loss function equation for the code.
  - Residual ( $f$ ): The difference between the Neural Network's second derivative and Newton's law.
  - $$f = \frac{d^2 \hat{y}}{dt^2} + \frac{\mu}{|\hat{y}|^3} \hat{y}$$
  - (Where  $\hat{y}$  is the network's predicted position).
- **Hyperparameter Tuning:** Determine the weight ( $\lambda$ ) for the physics loss. Start with  $\lambda = 1.0$ . If the model ignores data, lower it. If it ignores physics, raise it.

### Role: The Coder

- **Implement Autograd:** Use `torch.autograd.grad` to calculate the first derivative (velocity) and second derivative (acceleration) of the network output with respect to the input time ( $t$ ).
  - **Custom Loss Function:**
    - $$\text{Loss} = \text{MSE\_Data} + (\lambda * \text{MSE\_Physics\_Residual})$$
  - **Training:** Retrain the model.
  - **Validation:** Plot the new prediction for the final 20% of the orbit. It should now hug the true line much closer than the Phase 2 model.
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## Phase 4: High-Fidelity Upgrade (J2 Perturbation)

**Goal:** Increasing complexity to "Research Level." accounting for Earth's non-spherical shape.

### Role: The Mathematician

- **The J2 Formula:** Provide the Cartesian acceleration equations for the J2 perturbation (Earth's oblateness).
  - Note: This adds terms involving  $z^2$  and  $r^2$  to the acceleration equation.
- **Precession Analysis:** The orbit should now rotate (precess) slowly over time. Verify this behavior is mathematically expected.

### Role: The Coder

- **Update Physics Engine:** Update the Phase 1 generation script to include J2 acceleration so we have new "Ground Truth" data.
- **Update Loss Function:** Add the J2 terms to the PINN's physics loss function.
- **Long-Term Test:** Train on 1 orbit, predict 5 orbits. Show that the PINN captures the "wobble" (precession) that a standard neural network misses completely.

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## Phase 5: Metrics & Analysis

**Goal:** Generating the numbers and graphs for the presentation.

### Role: The Mathematician

- **Hamiltonian Check:** Calculate the Total Energy ( $H = \text{Kinetic} + \text{Potential}$ ) for every predicted point.
  - Plot  $H$  over time. The PINN should be nearly flat (conserved), while the standard NN fluctuates wildly.
- **Error Tables:** Create a table comparing RMSE for "Standard NN" vs "PINN" at  $t=100s$ ,  $t=1000s$ , and  $t=5000s$ .

### Role: The Coder

- **The "Money Shot" Plot:** Create a high-resolution 3D plot showing:
  1. Ground Truth (Solid Blue Line)
  2. Standard NN Prediction (Dotted Red Line - Diverging)
  3. PINN Prediction (Dashed Green Line - Accurate)
- **Code Cleanup:** Organize the code into a clean GitHub repository with a `README.md` explaining how to run it.

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## Phase 6: Deliverables

1. **Codebase:** *GitHub Repo with `generate_data.py`, `train_pinn.py`, and `plotting.py`.*
2. **Visuals:**
  - *Orbit Failure Plot (Phase 2).*
  - *Physics Loss Convergence Graph (Phase 3).*
  - *Energy Conservation Graph (Phase 5).*
3. **Abstract:** *A 250-word summary highlighting that PINNs reduce orbital propagation error by  $X\%$  compared to standard deep learning methods while enforcing physical laws.*